Europ. J. Agronomy xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

The interactions between genotype, management and environment in regional crop modelling

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ARTICLE INFO

Article history:
Received 2 January 2016
Received in revised form 10 May 2016
Accepted 10 May 2016
Available online xxx

Keywords:
Apsim
Corn
Clustering
Spatial modelling
Uncertainty
Sensitivity

ABSTRACT

Biophysical models to simulate crop yield are increasingly applied in regional climate impact assessments. When performing large-area simulations, there is often a paucity of data to spatially represent changes in genotype (G) and management (M) across different environments (E). The importance of this uncertainty source in simulation results is currently unclear. In this study, we used a variance-based sensitivity analysis to quantify the relative contribution of maize hybrid (i.e. G) and sowing date (i.e. M) to the variability in biomass yield (Y_T, total above-ground biomass) and harvest index (HI, fraction of grain in total yield) of irrigated silage maize, across the extent of arable lands in New Zealand (i.e. E). Using a locally calibrated crop model (APSIM-maize), 25 G x M scenarios were simulated at a 5 arc minute resolution (~5 km grid cell) using 30 years of historical weather data. Our results indicate that the impact of limited knowledge on G and M parameters depends on E and differs between model outputs. Specifically, the sensitivity of Y_T and HI to genotype and sowing date combinations showed different patterns across locations. The absolute impact of G and M factors was consistently greater in the colder southern regions of New Zealand. However, the relative share of total variability explained by each factor, the sensitivity index (S_i), showed distinct spatial patterns for the two output variables. The Y_T was more sensitive than HI in the warmer northern regions where absolute variability was the smallest. These patterns were characterised by a systematic response of S_i to environmental drivers. For example, the sensitivity of Y_T and HI to hybrid maturity consistently increased with temperature. For the irrigated conditions assumed in our study, inter-annual weather conditions explained a higher share of total variability in the southern colder regions. Our results suggest that the development of methods and datasets to more accurately represent spatio-temporal G and M variability can reduce uncertainty in regional modelling assessments at different degrees, depending on prevailing environmental conditions and the output variable of interest.

1. Introduction

Crop yield and quality are largely influenced by the interactions among genotype (G), management (M) and the growth environment (E) in agricultural systems (Hatfield and Walthall, 2015). These interactions are also represented in process-based biophysical models that are often used in climate risk assessments to simulate yield and quality of crops (Rosenzweig et al., 2013; Ewert et al., 2015). This implies that the confidence in simulation results depends on the accurate representation of crop varieties used (i.e. G) and crop management practices (i.e. M) applied by farmers. These decisions are mostly made at the scale of individual farms and therefore can widely vary in space and time (Ewert et al., 2011). When model simulations are performed across large areas (e.g. catchments, political regions or continents), there is often a paucity of data to represent variations in G and M parameters across different E conditions (e.g. multiple locations and years). The degree by which this uncertainty in input parameters is transferred to simulated results is unknown. This is particularly important for crops such as maize (*Zea mays*) that are cultivated over a wide range of climates and a diversity of production systems worldwide (Löffler et al., 2005; Ciampitti and Vyn, 2014).

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http://dx.doi.org/10.1016/j.eja.2016.05.005
1161-0301/

Two key input parameters that are set at the start of maize simulations are the hybrid maturity and the sowing date (Kucharik, 2003). These G and M parameters have an important bearing on the environmental conditions to which the crop will be exposed from sowing to harvest in any given location. While the sowing date determines the start of crop development, the hybrid class maturity regulates the rate of transition between successive development stages and consequently crop growth duration. Short-season hybrids require less time, often characterised by temperature accumulation requirements (i.e. thermal-time in degree-days, °Cd), to reach reproduction and maturity. Maize growers autonomously adapt sowing dates and hybrids to prevailing environmental conditions across years and locations (Kucharik, 2003). However, this spatial and temporal variation in G and M is rarely known when performing regional maize simulations. Although the importance of this uncertainty source has been recently highlighted (Ewert et al., 2015), to the best of our knowledge, there are no studies that have systematically investigated the topic.

In this study, we use a variance-based sensitivity analysis to quantify the effects carried through to large-area maize simulation results, due to incomplete knowledge about sowing dates and hybrid maturities, across multiple locations and years. Specifically, we set up a modelling experiment to estimate the share of total variability in maize productivity and quality across the extent of New Zealand arable lands. The geographic differences in climatic suitability for maize, from nearly optimal in the north to increasingly unsuitable for maize growth in the south, creates an ideal gradient to investigate spatial patterns of response to G and M input parameters. Results of this modelling study aim to inform agricultural risk assessments that rely on limited data to characterise genotype and management of silage maize crops across large areas.

2. Materials and methods

2.1. Site and weather data

The modelling study was performed across the extent of lands classified as "suitable for arable cropping" at a 5 arc minute resolution (~5 km grid cells) in New Zealand (Fig. 1). This included ~2760 grid cells that were selected based on the Land Use Capability classification at the Land Resource Information Systems (LRIS) Portal (Newsome et al., 2008). The selected land use classes ranged from no limitation (LUC Class 1) to moderate limitation (LUC Class 4) for arable cropping. For each grid cell, 30 years of historical daily weather data (1971–2000) were used as input to run a biophysical model (Fig. 1). The Virtual Climate Station Network (VCSN) weather data was obtained from the National Institute of Water and Atmospheric Research (NIWA) of New Zealand (Sood, 2015). The daily weather input variables used in the study were air temperature (°C, maximum and minimum), total solar radiation (MJ m^{-2}) and rainfall (mm).

2.2. Crop model description and testing

The release version of the maize module in the Agricultural Production Systems sIMulator (APSIM) version 7.7 (APSIM-maize) was used to perform all simulations (Holzworth et al., 2014). This modelling framework represents the response of underlying physiological processes (e.g. leaf appearance/expansion, light interception and biomass accumulation and partitioning among plant organs) of different crops to daily weather inputs and management interventions (e.g. sowing dates, fertiliser and irrigation applications). The maize model in APSIM has been previously documented (www.apsim.info/Documentation/) and applied across a large range of environments (Teixeira et al., 2010; Liu et al., 2012; Archontoulis et al., 2014; Teixeira et al., 2015). In this study, the model simulations were further compared with measured data from a "sowing date by hybrid maturity" field experiment (Sorensen et al., 2000) in Hawke's Bay, New Zealand (Fig. 1). The simulations for model testing considered management events reported in the field experiment and were performed in response to daily meteorological records measured at the experimental site. The treatments included ten different sowing dates (21 Sep to 20 Jan) and three hybrid maturities ranging from 77 to 114 units of Comparative Relative Maturity (CRM) used for classification of commercial hybrids (see Supplementary Material). The model fitness was evaluated by assessing the coefficient of determination (R^2) and the root mean squared deviation (RMSD, Eq. (1)) between observed and simulated values (Kobayashi and Salam, 2000) for total silage biomass yield (Y_T; i.e. above-ground dry matter containing leaves, stems, grains, rachis and husks), grain yield (Y_G) and the harvest index (HI).

Table 1
Parameterisation of the five hybrid types for New Zealand in APSIM-maize.

Hybrid type	tt_emerg_to_endjuv[a] (°Cd)	tt_flower_to_maturity[b] (°Cd)
Very early (h1)	130	850
Early (h2)	160	875
Mid (h3)	190	900
Late (h4)	220	925
Very late (h5)	250	950

[a] Thermal time from crop emergence to the end of the juvenile period.
[b] Thermal time from flowering to maturity. The thermal-time calculation was based on the piece-wise model by Wilson et al. (1995) used as default in APSIM-maize. The model linearly interpolates thermal-time estimates across the air temperatures of 0, 18, 26, 34 and 44Ĉ (x-axes) with corresponding thermal-time values of 0, 10, 18, 26, 0Ĉd (y-axes).

$$RMSD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - s_i)^2} \quad (1)$$

where n is the number of measurements, m_i is the measured value for observation i, and s_i is the simulated value for observation i. The results are presented as the relative RMSD (rRMSD, %) in relation to the observed mean value.

2.3. Simulation experiment

The simulation experiment was designed as a factorial combination of five sowing dates (1-Sep, 1-Oct, 1-Nov, 1-Dec and 1-Jan) and five hybrid maturities (Table 1). These combinations were developed to extend the sowing window slightly beyond the recommendations in seed company catalogues for New Zealand (see Supplementary Material). Recommended sowing dates range from 21 September to 3 December across most of New Zealand, with the exception of the southern regions where maize growth is constrained by low temperatures (Fig. 1). A wide range of hybrid maturities are recommended for each sowing date, depending on the climatic region. In general, very short-season hybrids are not recommended for early sowing in the northern (warmer) regions and very long-season hybrids are not recommended for the (colder) southern regions. Similarly, very early or very late sowing dates are not recommended for the most southern regions due to risk of spring and autumn frosts.

Five maturity rates were translated into two APSIM-maize parameters ("tt_emerg_to_endjuv" and "tt_flower_to_maturity") based on the comparative relative maturity (CRM, see Supplementary Material) of New Zealand commercial hybrids (Table 1).

Two model output variables were analysed, total silage biomass yield (Y_T) and the harvest index (HI). We used the HI to represent a quality aspect of maize silage because higher grain concentration